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WI-FI MEASUREMENT CAMPAIGN FOR INDOOR LOCALIZATION

Bachelor of Science Thesis

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ABSTRACT

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Most of the day to day people activities are carried out inside buildings. Many sectors such as, medicine, industry, academia or even security systems require indoor positioning services. As a consequence, it is essential to develop a reliable and accurate indoor positioning system (IPS). Since global navigation satellite systems (GNSSs) are not suitable for indoor localization, several IPSs have emerged. However, each indoor positioning technology has its advantages and disadvantages. Hence, there is not an IPS system with the best performance for every situation.

The IPS databases based on the Wi-Fi infrastructure installed in two buildings of the Tampere University of Technology required an update. Therefore, the scope of this thesis has been to update and moreover, optimize the IPS fingerprint databases of these two buildings. The results have been presented and analyzed with the expectance that they will be useful for similar or wider projects.

Multiple IPSs are explained, as it is convenient to understand the advantages and the weaknesses of each technology. The technology which provides the positioning services is the fingerprint Wi-Fi received signal strength (RSS). In that way, a measurement database is built. The database is used to simulate the IPS, which is implemented through the Bayesian estimation algorithm and the *k*-nearest neighbors technique. Successively, the parameters of the algorithm are optimized.

The analysis of the results showed that for the lowest values of the parameters, the performance of the system improves with respect to higher values of the parameters. The best performance of the Wi-Fi based IPS results in a floor detection probability nearby 99% and an average distance error below 3 m. However, negative effects, such as the ones produced by outlier measurements, must be taken into account. Some weaknesses of the Wi-Fi based IPS, such as the challenges associated to the training phase, open a path of research that might enhance the system performance.

PREFACE

This thesis was written in the Tampere University of Technology as the final work of my Bachelor Degree in Telecommunication Systems Engineering in the Polytechnic University of Madrid. Throughout the completion of the thesis I had to face several difficulties, which I used into my benefit to grow as an engineering student. Now that I am finishing my degree I am convinced that the skills acquired during this years and during the completion of the thesis will be useful for me in the future.

Nevertheless, the successful conclusion of the degree and of the thesis would not have been possible without the support of many people, to who I would like thank for their encouragement. First, I gratefully acknowledge my thesis supervisors, University Teacher Markus Allén and Assoc. Prof. Dr. Tech. Elena-Simona Lohan of the Tampere University of Technology for their helpful guidance and advices during the development of the thesis. I would like to thank the Polytechnic University of Madrid and the Erasmus program, which has given me the opportunity to develop my final work in a distinguished technology university.

My gratefulness is also to all the people I have met in Tampere, to my friends and to my family and relatives, who have been always providing me unconditional support in every decision I have taken.

Tampere, January 11, 2018

Alejandro González González

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LIST OF SYMBOLS AND ABBREVIATIONS

AP	Access point
AOA	Angle of arrival
CDF	Cumulative distribution function
GNSS	Global navigation satellite system
IPS	Indoor positioning system
ICI	Inter-cell interference
k-NN	k-nearest neighbors
LED	Light emitting diode
LOS	Line of sight
MAC address	Media access control address
PDF	Probability density function
RF	Radio frequency
RSS	Received signal strength
TDOA	Time difference of arrival
TOA	Time of arrival
TOF	Time of flight
VLC	Visible light communication
WLAN	Wireless local area network

d	Distance
μ	Mean
w	Noise
n	Path-loss factor
P_R	Received power of the signal
σ	Standard deviation
t	Time
P_T	Transmitted power of the signal
v	Velocity

1. INTRODUCTION

1.1 Thesis background

Positioning has always been important in our lives. Recently every time we visited a new place we most likely had a map in our hands. Nowadays it is hard to find someone using a physical map, mainly thanks to the smartphone technology progress. The smartphone has aided to extend the newest technologies to the society. As a consequence, the indoor positioning system (IPS) research lines have been focused on what the user needs. First, positioning has been focused on exteriors. However, given the large amount of activities that are carried out inside buildings, the main target of research has now switched to indoor positioning.

The development of indoor positioning technologies is the order of the day, as its market size is predicted to grow from EUR 5.72 billion in 2017 to EUR 33.02 billion by 2022 [26]. Global navigation satellite systems (GNSS) are widely used for outdoors positioning owing to their great performance, otherwise, for indoor positioning they are not broadly appropriate due to many complications such as, microwaves attenuation, signal dispersion or multipath effects, to which it has to be added the complexity of the triangulation inside the buildings [31, 5].

There are many technologies capable of giving a good positioning service and each one has its own line of investigation. However, none of these technologies is outperforming all others. Each system has its own advantages and problems. IPSs are mainly divided between non-radio technologies, such as magnetic positioning, inertial measurements, etc; and wireless technologies, such as angle of arrival (AOA), time of flight (TOF) or received signal strength (RSS) Wi-Fi positioning system. RSS is going to be the main topic of analysis in this thesis.

1.2 Thesis motivation

Wi-Fi based positioning system is a solid technology for indoor positioning. It is not the most used and developed IPS for nothing, but because it does not need any extra hardware to be installed. As the Wi-Fi infrastructure is available in most of the indoor locations, it can be exploited and used as the hardware infrastructure for the positioning system. Thereby, the IPS is carried out with a simple device such as a smartphone, which includes all the needed technologies necessary to communicate with the wireless local area network (WLAN) access points (APs) [5].

On the other hand, since Wi-Fi based IPS use radio signals to communicate with the user device, such IPS has to deal with some technical difficulties, such as floors, walls, furniture or people, that contribute to increase attenuation and fading. The process of collecting measurements for the fingerprint database is tedious and it usually takes a long time to gather enough measurements for the system to work with acceptable accuracy [5, 6].

The accuracy of Wi-Fi based positioning is very susceptible to changes in placement of the elements inside the buildings. This is the case of the measurements in some of the buildings of the Tampere University of Technology, where the measurements in the buildings 1 and 2 are outdated, therefore, the motivation of this Thesis has been to analyze the updating process of the measurements in building 1 and in building 2 and to optimize some of the positioning parameters used in Wi-Fi-based indoor positioning.

1.3 Thesis objectives

The main target of this thesis has been to improve the precision of the IPSs in the above-mentioned university buildings. This thesis will analyze and comment the improvements after updating the measurements. In order to understand the field and the diverse technologies, the different IPSs will be studied, focusing this thesis survey on the Wi-Fi and the fingerprinting method.

The future of Wi-Fi positioning is very promising and it has many possibilities of evolving. The main technologies that are pursuing the evolution of the indoor positioning will be presented.

1.4 Thesis structure

The thesis is divided into five chapters. The Chapter 2 represents the theoretical part of the thesis. In Chapter 2 the main indoor positioning technologies are presented. This chapter is particularly focused on the RSS Wi-Fi based IPS. Chapter 3 describes the measurement process of the RSS Wi-Fi method. Besides, different kind of measurements are presented. The analysis of the data and results is carried out in the Chapter 5. Furthermore, the optimization of the estimation algorithms is performed in that chapter. Chapter 6, contains the conclusions, which synthetize the main topics discussed in the thesis.

2. INDOOR POSITIONING TECHNOLOGIES

Several technologies have emerged and grown in order to solve the difficulties of indoor positioning due to the inefficiency of GNSS in indoor locations. Some of these technologies have become obsolete, whereas others are the most used in recent research projects, as they provide more efficient methods and higher quality results.

It is essential to recognize which parameters are distinctive in order to apply one technology or another. Some important attributes to take into account are location, exactitude requirements, economical limitations, accuracy, hardware, software, data collection process, etc.

2.1 Non-radio technologies

Regarding the indoor positioning technologies, the classification between non-radio technologies and wireless technologies is the most typical one. The non-radio methods embrace the ones that do not use the wireless infrastructure of the building, such as, magnetic positioning, inertial measurements, visual methods, etc.

2.1.1 Magnetic positioning

Magnetic phenomena have always been present in nature. Thales of Miletus was one of the first people that started thinking about the attributes of this phenomenon [8]. Nowadays, we use the properties of the magnetic and the electric fields for various purposes.

Some animals take advantage of Earth's magnetic field. For example, lobsters are capable of sensing the direction of the magnetic field and, what is more, they are even able to use it for navigation [4]. In last years, the IPS has had an approach based on the magnetic field [10].

It is known that a magnetic field can be created by a lot of elements, such as magnetic dipoles, electric currents, etc. Besides, some substances called ferromagnetic materials are very sensitive to magnetic fields, so they can easily interact with them. Thereby, the field imparts forces that affect other particles and objects [30].

In this case, the magnetic indoor technology takes advantage of the non-constant magnetic field created by the Earth. The magnetic field inside the buildings appears from both natural and human sources, due, mainly, to the steel and the structures with ferromagnetic properties of which the buildings are made. In addition, it is essential to consider the power systems that operate inside the buildings.

The professors Haverinen and Kemppainen of the university of Oulu have exposed that these anomalies provide a singular magnetic field depending on the positioning inside the building and it is called magnetic fingerprint [10]. The magnetic fingerprint is steady and reliable enough to grant a trustable measurement of the current position, unless one of the magnetic field modifiers changes; i.e., the structure of the building, power systems or machines, moving metal objects, etc.

Thus, the magnetic indoor positioning method is a complete and cost-effective solution, since the positioning method just requires a device with a magnetometer and a compass chip implemented inside it. The procedure of the positioning begins with a mapping process. It usually consists on specifying two points in a straight line, starting to collect magnetic measurements in one point and finishing in the other. Finally, it is fundamental to use an algorithm in order to estimate the position. Haverinen and Kemppainen introduce a Monte Carlo Localization technique as the estimation method in their study [10].

One of the biggest weaknesses of a pure magnetic-based IPS is the fact that it is not able to differentiate between floors with similar magnetic structure.

2.1.2 Inertial measurements

The indoor positioning based on inertial measurements method encompasses several techniques. The growth of the smartphone technology and the fact that almost everybody have a smartphone nowadays has aided to the evolution of indoor positioning inertial measurements. These devices incorporate magnetometers and accelerometers, which substitute the typical compass heading and pedometer respectively.

Most of these technologies demand specific requirements in furtherance of an acceptable performance, such as an initial, a fixed position and detailed map of the building, which is the case of the technologies related with dead reckoning [34].

Thereby, dead reckoning in outdoors has become useless due to the success of the GNSS, so it has evolved in order to be functional inside the buildings. It calculates the position of the subject by using a known initial position, or instead it can obtain the initial position by measuring external references (position fixing) and advancing that position a determinate distance regarding the speed of the subject, nevertheless, dead reckoning positioning methods tend to accumulate inaccuracies.

Inertial based indoor positioning is an economical technology, since no infrastructure is needed. On the other hand, a detailed building map is necessary to locate the subject. For solving that problem a simultaneous localization and mapping approach is proposed [13]. SLAM method allows to build a map of the building while providing the position to the subject in the same map [29].

This system could be suitable for buildings without the need of a complex infrastructure deployment. Otherwise, drift issues have been a big problem to deal with in the field of inertial devices but actually it can be alleviated by using particle filters. Sometimes, it is used with the support of wireless technologies to obtain an initial position. Some results of the research presented by Woodman and Harle (2008) [34] reveal that 0.73 m precision has been achieved for the 95% of the time without any initial position information. Thus, it uses the Wi-Fi signal to construct a radio map of the building. Afterwards, an approximate region of the map with the location of the subject is returned, although this is a combination between two different positioning technologies.

As it has been exposed in the previous procedure, inertial indoor positioning is usually used with other location technologies [12], it is worth pointing out that inertial positioning has been implemented for many purposes, such as emergency rescue location.

2.1.3 Positioning based on visual methods

Various indoor positioning technologies are based on the same techniques, such as the usage of a camera and the recognition of visual markers. Generally, the process of positioning based on visual methods implements two steps, the construction and the recognition of the visual marker.

The visual marker concept consists of an image captured by a camera and encoded afterwards as patterns composed by bits (generally 36 bits) and white or black squares depending on the light of the image zone. Several procedures are used for building and recognizing the marker, such as image thresholding, labeling, square checking, contour detecting and pattern matching. Being the image thresholding the first one applied [16, 23].

Variation of light causes a problem for construction and identification of visual markers. The principal solution is implemented by the adaptive thresholding method [15], which is capable of readjust the value of the pixels with a higher value than the admitted.

Augmented reality indoor positioning uses visual markers as well. However other methods are used complementarily to compare the results. A camera collects a sequence of images that is sent to a remote computer. The computer starts identifying visual markers and selecting the candidate markers, e.g., walls, doors or corridors [7, 16]. When a visual marker is founded in the candidates list, the location information of that visual marker is delivered to the user. The computing system also compares the sequence of images with its own image library and if it finds a similarity, another unit with positioning information is sent to the user. Both results are used for getting an accurate position.

2.1.4 Sound based positioning methods

Sound wave positioning methods are mainly divided based on the frequency of the sound wave i.e., ultrasound wave and audible sound. In this chapter the ultrasounds methods will be explained, since it is the most popular procedure.

Ultrasound is considered any sound wave above the frequencies of audible sound, meaning frequencies greater than 20 kHz. Ultrasonic location systems commonly use multiple beacons located in the ceiling emitting ultrasonic waves. Thereby, the mobile receiver is able to measure the time of arrival (TOA) between the different ultrasonic signals. Therefore, this technique makes use of multilateralization measuring and comparing the different times of arrival produced by the various sources [22]. Finally, the location of the subject is calculated using the known coordinates of the transmitters, the ultrasound speed and the times of arrival.

Diverse methods are developed regarding the above ultrasonic technique, some of them make use of radio frequency (RF) signals as support.

In the study of Addlesee et al. [1], the subject carries a device that transmits an ultrasonic wave when radio-triggered by a control mechanism. The system operates with multilateralization algorithms what makes it capable of giving an accuracy of 3 cm with an updating rate of 150 Hz.

Otherwise, the *Cricket* system proposed by Priyantha et al. (2000) [25], works in reverse. Multiple beacons are located across the building, each one emits an RF signal that carries information of the surrounding space, while sending ultrasonic vibrations at the same time. The transmitters broadcast randomly in order to avoid signal concurrence.

These two ultrasound positioning processes were narrowband methods; hence, they present various problems. Jamming is a big issue, since several transmitters send signals at the same time. The interferences between signals could spoil the process, to what we have to add the narrowband characteristic low data rate. This effect does not allow to encode a singular tag in short-duration signal, hindering the identification process. No solution has been implanted to overcome the ultrasound noise, that is generated in everyday actions.

Broadband alternatives have been proposed with optimistic results, giving a great performance in noisy environments, gathering quicker updating rates, grace to the simultaneous transmission from several emitters [12].

2.1.5 Positioning based on visible light communication (VLC)

Indoor positioning based on VLC is a method in process of development [21]. It applies the newest ideas and features of the VLC for indoor localization. It makes use of light emitting diodes (LEDs). LEDs have several advantages when performing VLC systems, such as, high efficiency, high response speed, etc. Since there are multiple methods to encrypt information using the visible light, this technology is very flexible. Luo et al. (2017) [21] propose three different methods to implement an IPS using VLC: 1) Mathematical method, 2) Sensor-assisted method and 3) Optimization method.

In order to provide positioning services, the system uses the light strength which is dependent on the number of light sources. Light strength can be measured bythe sensors installed in devices like a smartphone. Moreover, the light strength is steady which makes easier the process of updating and maintaining the system. Therefore, positioning based on VLC has various advantages. It can operate in places where RF systems cannot, it is less affected by multipath effects than other technologies and the accuracy of the system is up to a few centimeters, which is higher than other IPSs.

On the other hand, this system has to deal with various challenges. Given that multiple LEDs are installed in every of the rooms of the building, the inter-cell interference (ICI) appears. ICI is produced when LEDs working in the same frequency band are closed. Although positioning based on VLC is less affected by multipath effects than other technologies, it has to be considered. Multipath effects caused by reflections on different objects, may result in a decrease of the accuracy. One of the biggest weaknesses of these systems is the long delay when providing the localization information to the user.

2.2 Wireless technologies

Wireless systems have experimented an astounding progress in last years. Wireless technologies are present in many fields such as individual applications, medical systems, manufacturing, logistics, and vehicle systems next to many other appliances. Thanks to their usability, wireless systems are widely accessible in almost all locations. The need of an accurate indoor location system makes the wireless infrastructure a perfect implement to carry out the positioning in indoor and outdoor environments [11,24]. Usually, when the wireless system is used, the procedure of settling a location is called radiolocation.

Several studies of using Wi-Fi infrastructure for indoor positioning have resulted in various methods. The classification of these methods is based on: 1) The infrastructure used to carry out the location, i.e., wireless technology used to perform the link with mobile devices. 2) The method to calculate the location of the user, i.e., AOA, TOA and RSS [19].

2.2.1 Time of arrival and time difference of arrival technologies

TOA or TOF is considered the time that a radio signal takes to arrive from a transmitter to a receiver. Since the velocity of the signal is known and the signal carries the exact time when the transmission took place, it is possible to calculate the distance between the receiver and the transmitter by measuring the TOA and computing the following equation

$$d = \mathrm{c} \times \mathrm{t} \quad (m) \tag{1}$$

where c is the velocity of the light, d represents the distance between the APs and the device receiving the signal and t is the time that the signal takes to arrive to the device.

Therefore, the distance can be calculated solving this equation, but it does not provide enough information to pinpoint the user location. By using one more TOA measurements from another terminal, the position can be narrowed down to a pair of possible locations. Thus, to obtain a final accurate location, a third TOA data is needed, since it reduces all the possible location marks to a single point, as shows Figure 2.1 [18].

Unlike TOA, time difference of arrival (TDOA) does not use the absolute TOF between an emitter and a receiver. Instead, it calculates the TDOA of a signal forwarded by a single emitter to several receivers. When a signal is broadcasted to two different receivers, there is always going to be a small difference between the TOA measured in each receiver, which allows to obtain the TDOA [9]. Knowing the current locations of the two receivers, a bunch of locations matches the TDOA measure obtained. These possible solutions can be represented with a hyperboloid. A third receiver provides an extra TDOA measurement, which is dependent on the two previous TDOA. Therefore, the location is reduced to the intersection of two hyperboloids. A fourth receiver narrows down the possibilities, providing one or two locations. Logically, additional devices lead to greater accuracy in the system.

This system is limited by some issues. Indoor locations usually have various structures such as walls, roofs and furniture. These elements difficult the propagation of radio signals, mainly due to the multipath effect, which wrecks the functionality of the system, since its activity consist of measuring the TOF. Successively, TOA methods require a line of sight (LOS) between the transmitter and the receivers, which is really difficult to achieve in indoor locations [18].

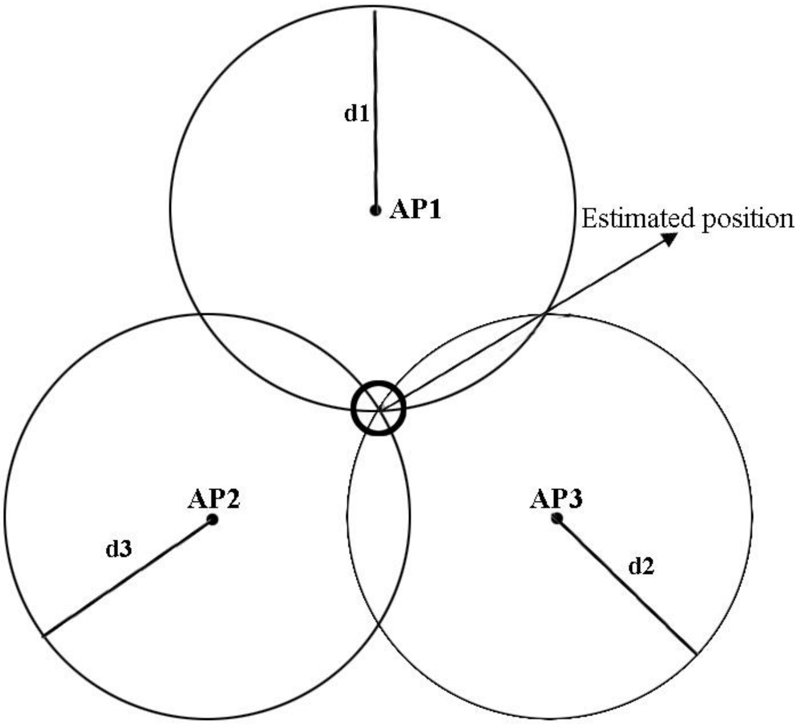

Figure 2.1. *Time of arrival estimation*

2.2.2 Technologies based on angle of arrival

AOA location technologies aim to determine the device position by measuring the direction of the mobile relative to an AP.

In order to measure the AOA, different options are available. The utilization of a mechanically actuated antenna is one of them, but usually is not the best implementation. Onthe other hand, the most suitable choice is the usage of an antenna array [33].

The purpose of this method is to obtain the direction of a radio signal that arrives to the antenna array. By using TDOA methods, the phase of the signal is measured in every single array element. Depending on the difference between phases, the AOA is estimated. Thereby, if the phase difference is zero, the angle of arrival is also 0º, while if the phase difference is 180º the angle of arrival would be 90º. By calculating multiple AOA in different antenna receivers, the location of the mobile can be estimated.

Several algorithms are implemented to estimate the AOA, such as the space-alternating generalized expectation-maximization algorithm or the maximum likelihood algorithm [33].

2.2.3 Wi-Fi received signal strength

In every communication a transmitter broadcasts a signal to a receiver. This signal can be characterized by several features; thus, an important attribute of the signal can be used: The received signal strength.

The RSS measures the power in decibel-milliwatts (dBm) of the incoming signal at the receiver. The RSS depends on the signal transmit power but also depends on more factors, such as the distance and the environment where the communication takes place.

Positioning based on Wi-Fi RSS is a wireless technique that offers a different approach than the previous wireless methods. Instead of using the propagation time or the AOA of the received signal, it uses the RSS based on sundry indoor attenuation models, such as the International Telecommunication Union model for indoor attenuation or log-distance path-loss model.

This technique can be used with one of the following 2 approaches: a) Trilateration based on path-loss model and b) Fingerprinting method.

Trilateration based on path-loss model

Trilateration consist in locating an object by measuring the distance between the object and three or more remote devices with known locations [3]. Given that the RSS is inversely proportional to the square of the distance and proportional to the emitted signal power, the distance between the AP and the receiver can be calculated as long as these two powers are measured.

Performing this process with two devices, one AP and one receiver, provides a bunch of possible locations describing a circle around the AP with known position. Successively, by using the same technique described in the TOA, with three or more APs we can narrow down the position of the target to one single localization. The weakness of trilateration lies in the difficulty of measuring the distance accurately since many objects in indoor locations generate difficulties in the propagation of the signal. Thereby, the distances are typically estimated according to a path-loss model as explained below.

The path-loss model requires two phases: the training phase and the estimation phase. In the training phase a big number of signal strength measurements are collected in order to build a RSS database. At this point a path-loss model can be used to determine the distance from multiple APs to the target point, by using trilateration the position of the target point is narrowed down [14]. A path-loss model based in indoor locations can be used. For example,

$$P_R(d) = P_T(d_0) - 10n\log(d/d_0) - \ w \cdot WAF + X_\sigma, \tag{2}$$

where $P_R\ (d)$ is the received power at the distance d, $P_T(d_0)$ is the power of the signal transmitted by the AP at the reference distance from the transmitter, n is the path-loss factor, d is the distance between the AP and the measurement point, d_0 is the reference distance, w represents the number of walls between the transmitter and the receiver, WAF is the wall attenuation factor and X_σ represents a random factor.

Thereby, the different RSS levels in the area can be calculated by using the previous path-loss equation. Successively, the calculated RSS is compared with the measured RSS by the user so as to determine the location [28].

Fingerprinting

The fingerprinting approach is used in this thesis to carry out the updating of the building measurements. This method is well known in the indoor positioning field and, as the RSS based on path-loss models, it involves a training phase and a positioning phase.

Training phase

The aim of the training phase is to create a fingerprint dataset. First, several points are carefully chosen as Reference Points (RPs). In each of these RPs the RSSs from multiple APs is measured and saved in the database, so each RP has a singular RSS called finger-print. The outcome of this phase is a fingerprint map (radio map) based on the database that shows the relation between the RPs and the RSS, as shows Figure 2.2 [17, 28].

The quality of the positioning systems largely depends on the number of fingerprints collected in the training phase. One of the great challenges regarding fingerprint methods is to optimize the data collection process. This is a long and tedious procedure where various trained individuals may spend a large number of hours collecting enough data for achieving an acceptable performance. Moreover, this data collection stage may be a very expensive procedure.

Several approaches have been proposed with the objective of optimizing the training phase. One of these methods is the fingerprint crowdsourcing, which shifts the data collection phase from trained surveyors to common users [20, 32]. Nevertheless, since the data collection based on crowdsourcing is not carried out by professional surveyors multiple drawbacks need to be overcome. Data collection in the correct RP location is no longer warranted. Another difficulty is the device diversity, as different devices have unlike accuracy. Wang et al (2016) [32] proposed an active fingerprint crowdsourcing method. The user participates actively in the data collection by providing positioning data. Alternatively, a passive fingerprint crowdsourcing is presented. In this method the user participates just by carrying a device capable of performance the measurements.

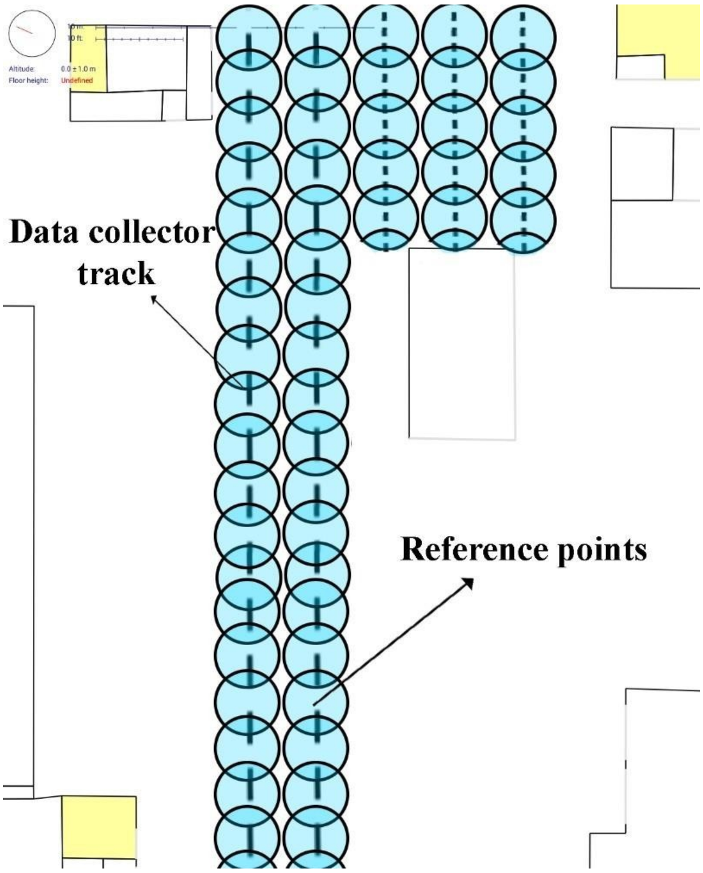

Figure 2.2 *Fingerprint radio map*

Positioning phase

In this phase the mobile user measures the RSS in its position. Then this measurement is compared with the fingerprint database. In turn, an algorithm is used in order to match a location registered in the database with the fingerprint collected by the mobile user.

Multiple search/match algorithms can be used to estimate the location of the mobile user. For example, studying the minimum difference between the measured RSS and the previously recorded RSS values, Euclidean distance, Sorensen, Gauss probability, methods based on machine learning, use of nearest neighbor average, etc.

K-nearest neighbors algorithm (*k*-NN) usually works with a fixed number of *k* neighbors. For each fingerprint measurement, *k* nearest neighbors are selected by measuring the distance between the current measurement and the fingerprints contained in the database. Successively, the selected nearest neighbors are analyzed, resulting in the estimated location of the fingerprint under study. Some recent research has determined that a variable K parameter could be useful in order to avoid further neighbors [27].

Two of the most important challenges, regarding the use of the Wi-Fi RSS for IPSs, are the noise effects and the harmful environmental factors that affects the signal in different ways. Usually, the radio signal used by the Wi-Fi system is propagated in the 2.4 GHz band, but it is not the only system using this band since other devices may use it, e.g., Bluetooth systems, microwaves, wireless phones, etc. As a result, the signal used for positioning is strongly polluted.

Furthermore, the RSS depends on several environmental factors, such as building structure, materials of the walls and ceilings, furniture disposition along corridors and rooms, people inside the building, etc. Therefore, all of these objects cause multiple impacts affecting the quality of the signal, such as reflection, refraction, diffraction and absorption. Thus, the signal experiments diverse harmful effects, e.g., path-loss, multipath fading, etc.

Comparison between fingerprint and trilateration based on path-loss model

Trilateration and path-loss approaches are based on propagation models. In this way a radio propagation model is built in order to estimate the distance from multiple APs to the point where the user is collecting measurements. Since, these methods provide distance approximation, they are not able to provide high accuracy measurements, mainly due to the effects of the environment.

On the other hand, fingerprinting approach usually performs better, given that it uses a database which stores RSS measurements given by multiple APs, while trilateration uses three APs. Fingerprinting positioning procedure allows to implement various estimation algorithms that are able to analyze in different ways the measurements, which contributes to a better performance and provides a higher freedom for developing or improving estimation algorithms.

In this way, indoor positioning based on wireless technologies and specially fingerprinting approach has become the most popular implementation for indoor localization. Given that, the wireless infrastructure is available in the majority of the buildings, it does not require extra hardware installation. Nonetheless, the accuracy of this system is commonly lower than the achieved with TOA, AOA and TDOA and it is also very environment dependent and time consuming.

3. MEASUREMENT PROCESS

As it has been described previously, the Wi-Fi RSS IPS is highly conditioned by changes of the environment. The system used in this study has been focused is the Wi-Fi fingerprint RSS. Thereupon, an update of the fingerprint database it is needed, as well as an optimization of the parameters used for the location estimation.

The measurement collection phase has taken place in two buildings of the Tampere University of Technology. The buildings will be named during the rest of this thesis as building 1 and building 2. Both buildings include several floors, long corridors, small rooms, and bigger size rooms. In the majority of the cases, the measurement collection process has avoided to take measurements in the smallest rooms.

In the measurement phase, various tools have been essential. A proprietary Android software data collection tool installed on a Nexus tablet was used to collect the measurements. This software provides different functionalities. It allows to load different maps with linked coordinates information. Besides, it presents a map view interface which makes easier the measurement collection process. It also presents the RSS fingerprints as green circles. In order to process the data collected with the Indoor Survey Tool various Matlab functions and scripts have been used. In the measurement collection process several types of measurements are needed in order to build an accurate up to date database.

Standard measurements

Standard measurements refer to the measurements with which the RSS fingerprint data-base is built. The indoor survey tool collects the measurements and store them as a text file. The information contained in each text file gathers the media access control addresses (MAC addresses), the RSS, the frequency of the signal, calibration data and information regarding the building. These MAC addresses identify the APs, whose signal is detected by the measurement collector device. The value of the measured RSS is linked to the coordinates information of each location. The working frequencies vary depending of the APs. They are within the industrial, scientific and medical radio bands used for Wi-Fi, which are the 2.4 GHz and the 5 GHz bands.

The process of collecting the RSS measurements requires to walk through the target space collecting measurements as many spaces as possible. It is needed to follow a straight

Figure 3.1 *Visual records of lecture room*

line while capturing the RSS. When the data collector faces a wall, the current RSS measurement series needs to be stopped and saved. A new measurement series is started in another direction, until the target space is completed.

In the process of collecting RSS measurements is essential to keep a constant walking speed. The slower the data capture speed, the higher the quality of the measurement. It is fundamental to consider the structure of the space to be measured in order to collect the data in an effective way. Thus, in the process of measuring rooms with a lot of furniture, where it is impossible to carry out a complete data collection, a measurement strategy is necessary. For instance, lecture rooms with a lot of tables and chairs have been measured by following the main corridors and some perpendicular lines between them as shows Figure 3.1.

After a measurement collecting session all the obtained measurements are saved as a .txt file in the device. In order to avoid overlapping issues between measurements, the data is deleted from the proprietary software used in data collection.

Records

It is important to have an up to date record of the measurements taken in each session. Thereby, during this thesis work, after every measurement collecting session, a record with valuable information about the measurements has been taken.

The record files store information such as, the place where the measurement colleting session took place, the day and the approximate time, etc. This information has been useful to analyze the measurement data, which is often dependent of these factors. But it is also helpful to solve problems such as measurement overlapping.

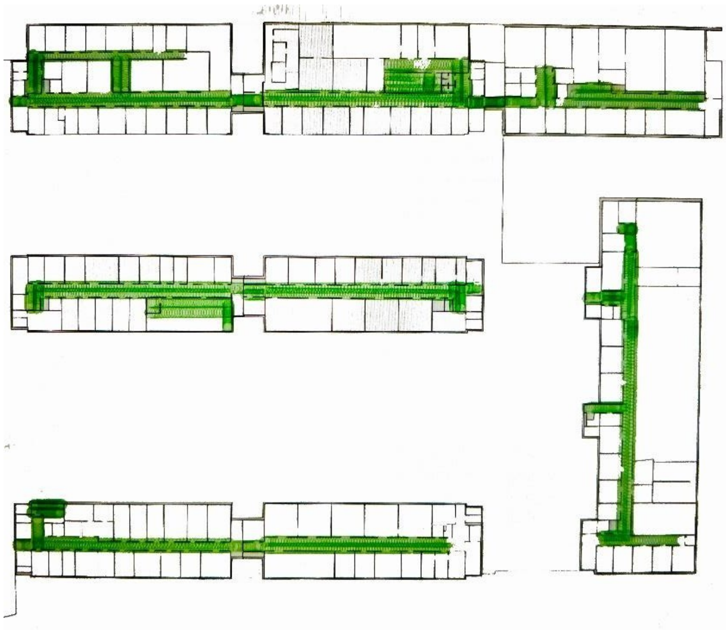

Figure 3.2. Measurement session covered area record

In that way, there are two types of records, the written record and the visual record. The written record, stores the measured places, the date and the hour. The visual record presents visual information, such as photos of rooms and corridors that are useful to interpret the RSS measurements as shows the Figure 3.1. Besides, it has resulted useful to store images of the screen of the device showing the map with all the fingerprints taken in each measurement session as shows the Figure 3.2.

Tracks measurements

These measurements have been used for testing purposes. It is useful to have some results that allow to filter and classify the standard measurements. These measurements test multiple factors that can affect and change the quality of the measurements, such as, different data collection speeds, different heights and positions of the data capturing device, etc.

The track measurements consist of single straight tracks taken in corridors or rooms with the aim of testing the results with different speeds, heights and inclinations of the device. These measurements have been saved and analyzed afterwards as a support to understand the standard measurements. A few track measurements are needed to obtain useful results. Nevertheless, it is not needed a measurement database track as large as the standard measurement database.

4. MEASUREMENT ANALYSIS AND OPTIMIZATION

The next step after completing the database is to analyze the measurements. There by, it is possible to obtain valuable information allowing us to optimize the estimation algorithm. The optimization process is essential, resulting in an improvement of the system accuracy.

The database collected in the measurement process results to be the training data. This collected data trains the positioning system. It provides estimated positions for the users regarding the measured RSS. However, prior to this, the measurement database is divided between training data and test data. Furthermore, the algorithm parameters are changed, in the way that different results can be compared.

The estimation phase makes use of two methods. Both methods have their own purpose. In first instance, a Bayesian based algorithm is used. The Bayesian algorithm computes the probability of each RSS measurement point to match with the current RSS measurement obtained by the user. The probability is calculated by employing the gaussian similarity method. The gaussian similarity requires to use the gaussian probability density function (PDF) for each measured point,

$$\mathrm{PDF} = \frac{1}{\sqrt{2\pi\sigma^2}} e^{\frac{(x-\mu)^2}{2\sigma^2}} \tag{3}$$

where the σ is the standard deviation and represents the deviation of the RSS, the x represents each RSS measurement of the training database from which it is required to calculate the probability of matching and μ is the RSS value of the current measurement. The standard deviation turns to be the only parameter that can be modified and hence, optimized. The PDF is computed for every AP in range. Subsequently, the information coming from all APs is summed in logarithmic scale and lastly the logarithmic likelihood function is maximized.

Once the Bayesian algorithm has been applied, the following step is to use a k-NN algorithm. This algorithm selects the K points with the highest probability and computes the mean of their coordinates. This process results on the estimated position for the current measurement point. In this second method the parameter K can be optimized. Thereby, selecting a different number of neighbors may result in a different accuracy of the system.

The performance quality of the positioning system can be assessed in two directions. First, the floor detection probability measures the success rate when classifying measurement points by floors. In order to make that estimation, the height of each floor is subtracted to the z-coordinate of the measurement point. Successively, the floor height that provides the smallest value for the subtraction is selected. On the other hand, the mean distance error represents the mean error between all the estimated positions for the measurement points and the corresponding real position of the points. The optimization process is carried out by trying out different combinations of values for the RSS deviation and for the number of neighbors. Different values may result in higher accuracy for the floor detection probability than for the mean distance error and vice versa. Thus, the purpose is to achieve a balance of accuracy for these two features. In a first approach, good results for the floor detection probability and for the mean distance error have been obtained using a small number of neighbors, such as, one, two or three as show the Table 1 and the Table 2. The best results are represented by dark red, moderate results by pink and white represents worst values.

The first table shows that the floor detection probability increases for the lowest values of neighbors, while it is constant for the sigma deviation values. The Table 2 shows that the mean distance error decrease for the lowest numbers of neighbors and for the lowest values of sigma deviation. Based on the values presented on Table 1 and Table 2, the most suitable values for the best floor detection performance are 3 dB of sigma deviation and 2 neighbors. Otherwise, for achieving the lowest mean distance error the suitable values are 2 dB for the sigma deviation and 1 neighbor. The appropriate choice depends on the situation and on the final purpose of the system.

Table 1. *Floor detection probability in building 1*

Sigma / Neighbors	2	3	4	5	6
1	99.7876	99.7876	99.8262	99.8262	99.8262
2	99.8841	99.9227	99.9227	99.9227	99.9227
3	99.749	99.8069	99.7876	99.7683	99.7683
4	99.7683	99.7876	99.7876	99.7876	99.7876
5	99.7104	99.7683	99.749	99.7297	99.7297
6	99.5559	99.7104	99.749	99.7104	99.6911

Table 2. *Mean distance error in building 1 in meters*

Sigma / Neighbors	2	3	4	5	6
1	1.8679	1.9564	2.1289	2.3107	2.4934
2	2.1399	2.2697	2.4616	2.6623	2.8433
3	2.4253	2.582	2.7543	2.9401	3.1225
4	2.6624	2.7728	2.9649	3.1628	3.3188
5	2.8536	2.9197	3.0953	3.2894	3.4653
6	3.0119	3.0308	3.2119	3.4169	3.5975

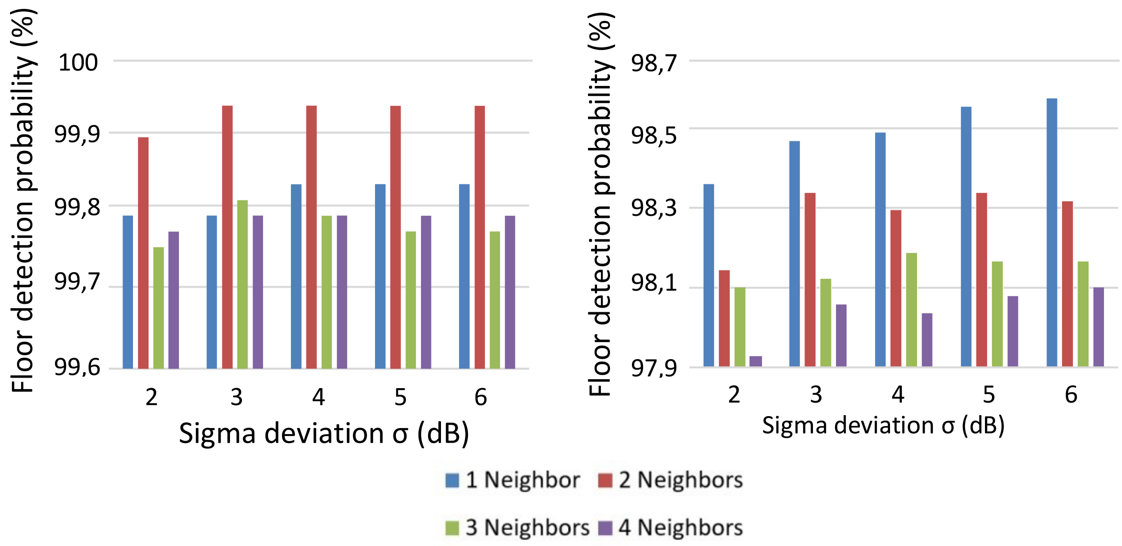

Figure 4.1. *Floor detection probability for buildings 1 and 2 respectively*

Figure 4.1 presents the probability of floor detection for the building 1 and for the building 2. Both buildings have better performance for the lowest number of neighbors as it has been analyzed before. The success probability when classifying the measurements by floors is higher for the building 1 than for the building 2. The variation of floor detection probability between both buildings might be due to the amount of measurements collected for each building.

As can be seen, in the building 1 the success probability reaches values over 99.9% using two neighbors for the *k*-NN algorithm. For other values of neighbors, such as one, three or four, the floor detection probability is nearby 99.8%. On the other hand, this feature is relatively constant for different values of sigma deviation.

Otherwise, the best performance of the floor detection probability for the building 2 is obtained using one neighbor. In this case, incrementing the value of the sigma deviation results in an increase of the floor detection probability. The highest value is nearby 98.6%, and is obtained for a deviation of 6 dB. It is worth to highlight that using 2 neighbors provides better results than using three, four or more neighbors.

In another way, the mean distance error presents different results for similar values of neighbors and sigma deviation. First, it is essential to interpret correctly the values of the mean distance error. Low values of the mean distance error indicate that the estimated position is close to the real position, while higher values of that parameter denote that the overall of the estimated positions are far to the real positions. Successively, the lowest the value of the mean distance error is, the better the performance and the accuracy of the positioning system.

As it can be seen in the Figure 4.2, the values obtained for the mean distance error reveal different results to those obtained for the floor detection probability. This analysis shows that the mean distance error average obtained for the building 2 is higher than the one obtained for the building 1. However, the mean distance error obtained for the building 1

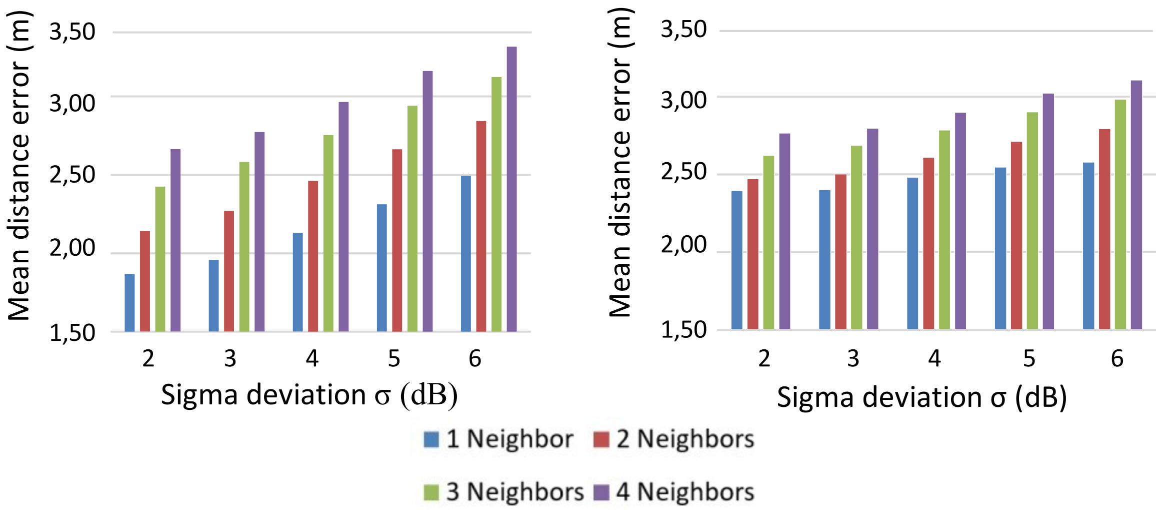

Figure 4.2. *Mean distance error for buildings 1 and 2 respectively*

is highly dependent on the number of neighbors, while the mean distance error obtained for the building 2 is steadier.

The left figure represents the performance of the system for the building one. It shows that the mean distance error increases for the highest values of sigma deviation and for the highest number of neighbors as well. By using one neighbor and a value of 2 dB for the sigma deviation results in a mean distance error of 1.8 m. Incrementing the number of neighbors deteriorates the accuracy of the algorithm more than incrementing the value of the sigma deviation.

The figure on the right shows that system behaves more consistently in the building 2. It is less dependent on varying the number of neighbors and the value of the sigma deviation. The lowest mean distance error value for the building 2 is nearby 2.4 m. It is worth pointing out that for the building 2 the difference between the highest value and the lowest values of the mean distance error is approximately 0.7 m. On the other hand, the same difference for the building 1 is 1.5 m, which is almost the double.

In order to achieve a better understanding of the results, it is useful to make use of the cumulative distribution function (CDF). The CDF may lead to new results and valuable information that could remain hidden with another type of analysis. The CDF is defined by,

$$F_x(x) = P(X \leq x), \tag{4}$$

and it computes the probability that a variable X will take a value lower or equal to x. Therefore, several parameters and features of the data can be obtained using the CDF, such as, the mean value, the variance, etc.

The Figure 4.3 presents the CDFs for the mean square error obtained with different values of the number of neighbors and of the sigma deviation. The graphic on the left shows the CDFs obtained for the building 1. The parameters have been selected with the purpose of obtaining different results. The blue line represents the CDF

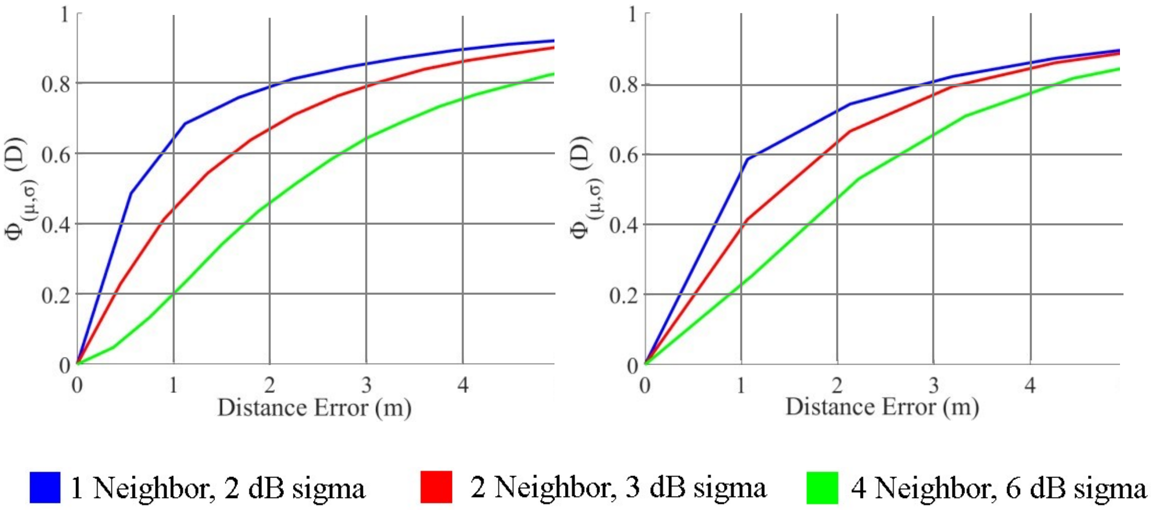

Figure 4.3. *Cumulative density function of the distance error for the building 1 and the building 2 respectively.*

obtained with the parameters providing the best results. On the other hand, the red line and the green line represent the CDFs obtained with parameters which provide worse results.

As it can be observed, the data associated to the blue CDF have a low mean value and the variance is small as well. This graphic shows that the probability of a distance error lower than 2 meters is about 80%. In another way, the variance is bigger for the data associated to the red and to the green plot of the CDF. In contrast with the previous analysis, the probabilities of a distance error below 2 meters are nearby 65% and 45% for the red plot and the green plot of the CDF respectively.

The figure on the right represents the CDFs of the distance error for the building 2. The results are similar, given that the parameters have been selected with the same criteria that for the building 1. As it can be observed, the variance is bigger for the CDFs associated to the building 2. This fact denotes that distance error is more inconstant for this location. Furthermore, in average the distance error is bigger for the building 2.

In both buildings the best results have been obtained for the lowest values of the number of neighbors and of the sigma deviation. Nonetheless, low values for that parameters implies a high risk of doing a bad prediction for some measurements due to the possible appearance of outliers. An outlier is a point which is remote from other similar measurements as consequence of an irregular measurement or an error in the collection phase. Selecting one or two neighbors may avoid some valuable information, since the nearest fingerprint could be an inaccurate fingerprint. Otherwise, higher number of neighbors takes into account more information minimizing the effect of possible wrong fingerprints.

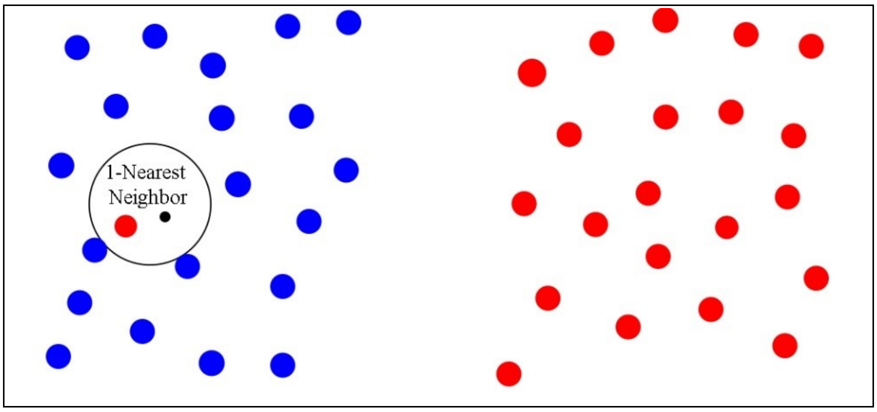

Figure 4.4. *Measurement prediction using 1-nearest neighbor algorithm*

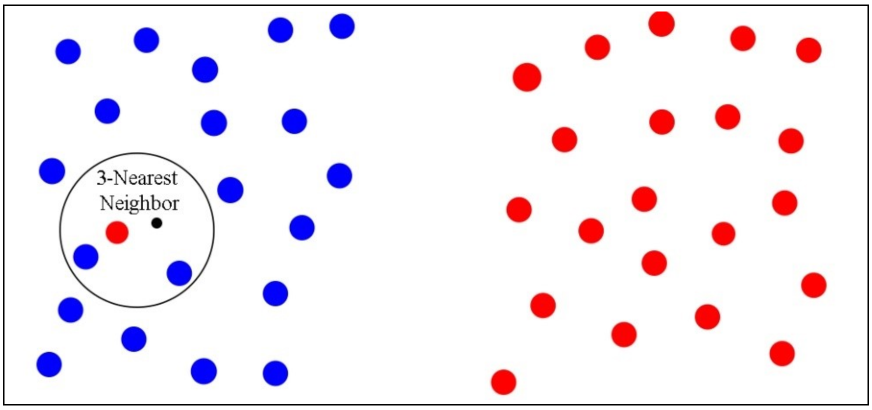

Figure 4.5. *Measurement prediction using 3-nearest neighbor algorithm*

As shows Figure 4.4, for 1 neighbor the system may predict a point as a red dot where the distribution shows that the percentage of belonging to the blue dots distribution is much higher than to the red dots. On the other hand, using 3 neighbors may avoid this issue, since it takes into account more points than the 1-neighbor approach as shows Figure 4.5. As a consequence, a higher number of neighbors results in a reliable model, while for 1 neighbor the probability of a bad prediction is higher but the accuracy for the good prediction is better than for more neighbors.

Given the analyzed results, the selected algorithm parameters depend on the expected performance of the system. With the aim of achieving a good performance for the floor detection probability, the most suitable parameters for the building 1 and for the building 2 are presented in the Table 3. Even though, the best results are obtained for 1 neighbor, it is a good choice to select 3 neighbors, since it avoids the issues generated by the outliers. Whereas the value of the sigma deviation for the building 1 and for the building 2 is 3 and 4 respectively. It is worth noting that it is not advisable to select an even number of nearest neighbors, as there can be a draw between the nearest neighbors. On the other hand, with the objective of achieving a good value for the mean distance error, the most suitable algorithm parameters are presented in the Table 4. For both buildings, the selected number of neighbors is 3 and the value of the sigma deviation is 2

Table 3. *Algorithm parameters for a successful floor detection probability*

Building	***k*-nearest neighbors (k)**	**Sigma deviation (dB)**
Building 1	3	3
Building 2	3	4

Table 4. *Algorithm parameters for a successful mean distance error*

Building	***k*-nearest neighbors (k)**	**Sigma deviation (dB)**
Building 1	3	2
Building 2	3	2

5. CONCLUSIONS

From the use of physical maps to the appearance of multiple indoor positioning technologies this field of research has evolved in a great manner. These IPSs are useful in the day to day life, as they smooth the progress of the activities of the people inside the buildings. Given the fact that every building is different and every circumstance requires different solutions, each technology tries to solve diverse situations.

Indoor localization technologies are leading the market of the positioning systems. Technologies, such as, magnetic positioning and visible light communication, show the great economic and research potential of this field. Among all the indoor positioning technologies the Wi-Fi fingerprint RSS is a solid and reliable technique. It provides an acceptable accuracy and its performance has been shown in multiple circumstances. On the other hand, the quality of this technique is highly dependent on changes in the environment. Besides, the training phase of the system is a tedious and very time-consuming activity.

The results have shown that the accuracy of the fingerprint method increases with large measurement databases. Hence, the training phase of the system is essential. Nevertheless, the performance of the system does not just depend on the number of measurements, it also relies on the estimation method and its parameters. Thus, the accuracy can be improved by studying and analyzing the system behavior with different parameters. The system has presented the best performance for low values of the number of neighbors and of the sigma deviation. However, this analysis requires further research, given that low values of the parameters may lead to overfitting problems.

The weaknesses of the fingerprint method open multiple fields of research, such as crowdsourcing techniques, which will keep evolving in the next years. In the same way, the evolution of the estimation algorithms based on machine learning techniques is aiding the growth of IPSs.

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